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THE RELATIVE RISK PERFORMANCE OF ISLAMIC FINANCE: A NEW GUIDE TO LESS RISKY INVESTMENTS

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We examine the relative risk performance of the Dow Jones Islamic Index (DJIS) and find that the index outperforms the Dow Jones (DJIM) WORLD Index in terms of risk. Using the most recent Value-at-Risk (VaR) methodologies (RiskMetrics, Student-t APARCH, and skewed Student-t APARCH) on the 1996–2005 period, and assuming one-day holding period for both indices with a moving window of 500 day data, we show that the value of VaR is greater for DJIM WORLD than for DJIS Islamic. We interpret the results mainly to the profit-and-loss sharing principle of Islamic finance where banks share the profits and bear losses (Mudarabah) or share both profits and losses (Musharaka) with the firm.

Keywords: Islamic investment; profit-and-loss sharing; risk performance; Value-at-Risk.

1. Introduction

During the last decade, the Islamic finance has gained significant attention due to its size, fast-paced growth, and the potential impact on the international financial markets. The worldwide estimates of Islamic finance range from $230 billion to nearly $250 billion. With a projected annual growth rate in assets of 12–15%, the market potential has been estimated at close to 10% of global domestic product (GDP) [7]. Furthermore, Islamic capital invested in global financial institutions is currently estimated at $1.3 trillion, and over 105 Islamic equity funds globally are managed assets in excess of $3.5 billion.

To tap into the significant business markets and to meet the increasing demands of customer, a growing number of conventional financial institutions established their own Islamic financial instruments and portfolios. One such product is the Dow Jones Islamic Market World Index (DJIS), which tracks Shari'ah compliant stocks from around the world, providing Islamic investors with comprehensive tools based

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on a truly global investing perspective. The index is a basket of stocks acceptable to Islamic principles (shunning unethical or highly indebted firms, or firms engaged in gambling, alcohol sales, and other prohibited activities with respect to Islam). A parallel and unrestricted counterpart of the Dow Jones Islamic Index (DJIS) is the Dow Jones (DJIM) WORLD Index, which is a comprehensive world index family, designed to provide international investors with a complete range of a portfolio management and benchmarking tools which include over 1800 components worldwide diversified across 34 countries, 10 economic sectors, 18 market sectors, and 51 industry groups. The DJIS is an Islamic equity benchmark index and a subset of the DJIM. Of the DJIM index, 65% of the companies fail to meet the Islamic criteria, leaving only approximately 1934 companies with $1.2 trillion total market capitalization (representing 41% of the global market capitalization) as potential candidates for the inclusion in the DJIS.

The rapid propagation and remarkable growth of Islamic investments has also placed an additional necessity to better understand their risk profile. In this paper, we fill the gap in the literature by using the recent risk model, the so-called Value-at-Risk (VaR), to examine how Sharia restriction affects the risk of Islamic investments represented by the DJIS.[1] The motivation is that the profit-and-loss sharing (PLS) principle of Islamic finance is based on the Mudarabah principle in which the financier provides the entrepreneur with capital for some business on the condition that profits generated will be shared between them. However, if the entrepreneur experiences a loss in the course of business and not due to misconduct in his/her part, then the financier will bear that loss. Another form of PLS is Musharaka, where the financier and the firm jointly provide the capital, and manage the project, and they jointly share both profits and losses (see [1] for further discussion). Incorporating this information into the analysis, we claim that the PLS mechanism will be superior to the western type finance in terms of risk. The motivation for claiming risk reduction is fourfold. First, the Islamic firm will provide lower contingent-payoffs in good states and higher contingent-payoffs in bad states for shareholders in comparison to the free market non-Islamic firm. In good states, when the firm experiences a profit, the financier will share the profit with the firm. The profit sharing rate in which profits are distributed is ex-ante and provides higher returns for the financier than interest rates. As a result, the shareholders of the Islamic firm will experience lower returns than the shareholders of the non-Islamic levered firm. However, in bad states, when the firm experiences a loss, the financier will bear the whole loss and shareholders bear nothing.[2] The result of this returns behavior is a potential preference of the Islamic firm, as investors in the Islamic firm have less volatile payoffs in comparison to the non-Islamic firm.

[1]To our knowledge, this is the first empirical study in the literature of the emergent Islamic investments, which emphasize the estimation of the risk profile of Islamic stock indexes.

[2]In case of Musharaka, the financier will partly share the loss with the firm. The same conclusion can be gleaned if the firm uses Mudarabah to finance the project.

Second, agency costs in external credit markets come from a divergence of incentives between the borrower (the firm) and the lender (the bank) when the lender cannot fully monitor the borrower's behavior. The reason is that the opportunity cost of a project is small for a firm which borrows most or all of the funds to finance it, while the gains from a successful outcome may be high (e.g., [2, 3, 14]). In the PLS system, the bank will provide the entrepreneur with funds only if the project has low level of risk since it shares the loss. However, traditional banks, which conduct debt contracts, may seek financing for lower quality projects than the Islamic bank. This seems to suggest that the PLS system will constrain the set of the projects to which it finances to the profitable projects. This can be interpreted as saying that the PLS system may reduce the overinvestment problem by using the strong motive for the bank to monitor the project.

Third, the traditional view of the picking order theory of Myers [23] and Myers and Majulf [24] suggests that firms have a preference ranking over financing sources because of asymmetric information between managers and investors. Managers tend to finance through equity when it is overpriced, but investors aware of managers' incentives buy the securities that they are willing to hold at discount. The result of this discounting is a potential underinvestment problem, as managers forgo positive investment opportunities. Managers work their way up the pecking order to finance investment, beginning with returned earnings, followed by debt, and then equity, in an attempt to minimize adverse selection costs. According to the Myers [23] and Myers and Majulf [24] modified (or dynamic) picking order hypothesis, firms may issue securities instead of debt or internal financing to preserve liquidity and debt capacity for future potential investment, thereby issuing equity to avoid potential underinvestment problem and lower expected bankruptcy costs. Depositors in Islamic banking can be compared to investors or shareholders, who earn dividends when the bank makes a profit or lose part of their savings if the bank announces a loss. Thus, the PLS system may decrease expected bankruptcy costs of the firm.[3]

Finally, the shift to the PLS system will eliminate conflicts between equityholders and debtholders such as the asset substitution problem. The asset substitution problem results from the incentive of equity holders to take out value from debtholders by accepting risky negative net present value projects [17, 21, 22, 27]. This implies a decrease of the value of the firm, as a result of a decrease of the value of the debt and a smaller increase of the value of the equity. This free ride behavior of equityholders is integrated into the price of debt, and the ex-ante solution to this agency problem is therefore to issue less debt. Quoting the economic

[3]Titman and Wessels [29], Chaplinsky and Niehaus [5], Rajan and Zingales [26], and Fama and French [9, 10] present evidence that profitability is negatively associated with leverage since better quality firms can more easily finance investment with equity instead of debt. Strebulaev [28] develops an equilibrium model of capital structure that generates a negative profitability–leverage association consistent with the picking order.

rationale of the PLS system illustrated by the International Association of Islamic Banks [15], "If interest is replaced by profit sharing, some imbalances are expected to be reduced. First, the return on capital will depend on productivity. Allocation of investable funds will be guided by the soundness of the project. This will in effect improve the capital allocation." Aggrawal and Yousef [1] interpret this quote as stating that interest-free financing techniques eliminate conflicts between equityholders and debtholders such as the asset substitution problem. They develop a model of investment and capital structure based on incomplete contracts. They show that if the asset substitution costs are high, then a ban on debt can be social welfare improving.[4]

We perform two symmetric (RiskMetrics and Student-t APARCH) models and one asymmetric (skewed Student-t APARCH) model to estimate risk-measures for both indices. Assuming a one-day holding period and using a moving window of 500 day data, our results show that the Dow Jones Islamic Index (DJIS) outperforms the Dow Jones (DJIM) WORLD Index in terms of risk. It appears that the filtering criteria adopted to eliminate Shari'ah-non-compliant companies have resulted in a subset of unique companies and did not adversely affect the performance of the Islamic index in comparison to the world equity market.

The paper is organized as follows. In Sec. 2, various VaR models and the reality check are discussed. Section 3 presents the data and their descriptive statistics. Section 4 reports the empirical results and Sec. 5 concludes.

2. VaR Methodologies

The VaR model can be generally defined as a quantitative tool whose objective is to asses the potential loss that can be incurred by a financial institution over a given time period and for a given portfolio of assets. In the context of market risk, VaR measures the market value exposure of a financial instrument in case tomorrow is a statistically defined bad day. VaR's popularity and widespread use in financial institutions stem from its easy-to-understand definition and the fact that it aggregates the likely loss of a portfolio of assets into a number expressed in percent or in nominal amount of a chosen currency. Furthermore, VaR also can be used to qualify the risk-return profile of active market participants such as traders or asset managers.[5]

Although a single, robust, and clear definition of VaR may be given, the exact method of implementing VaR is far from being settled. By its nature, VaR estimation is highly dependent on good predictions of uncommon events or disastrous risk. Thus, it is vital to model the returns distribution as accurately as possible. The traditional methods to model the returns distributions include (1) the parametric method (analytic based); (2) historical simulation; (3) Monte Carlo simulation;

[4]They show that this result can also be generalized to other costs associated with debt as well. Default and liquidation costs, adverse selection, and costs associated with bankruptcy and financial distress can affect the welfare improvement in the same way that asset substitution does.
[5]For more information about VaR techniques and regulation issues see, for example, [18].

and (4) the stress testing (scenario analysis). However, modeling of financial time series data is not trouble-free to task because they possess some particular characteristics. They often exhibit volatility clustering (i.e., returns go through periods of high and low variance), which, towards what is called the time-varying conditional variance, often exhibit leptokurtosis (i.e., the distribution of their returns is fat tailed), and often show leverage effect (i.e., changes in stock prices tend to be negatively correlated with changes in volatility). The two characteristics have been modeled successfully in the financial econometrics literature by the use of the generalized autoregressive conditionally heteroskedastic (GARCH) model developed by Bollerslev [4]. However, since the distribution of this model is assumed asymmetric, it fails to fully capture the third characteristic. This led to the development of many nonlinear extensions of the GARCH model, including exponential GARCH (EGARCH) of Nelson [25] and the asymmetric power ARCH (APARCH) of Ding *et al.* [11]. However, in practice, these models fail to fully capture thick tail properties of financial time series. To capture the skewness and kurtosis, Fernandez and Steel [11] induced the skewed Student-t distribution, and more recently, Lambert and Laurent [20] extended this to the GARCH model. Giot and Laurent [12, 13] estimate VaR for daily stock index returns using the APARCH model with normal distribution, Student-t distribution, and skewed Student-t distribution. They concluded that models based on the symmetric density distribution underperform the one based on a skewed density distribution. They, therefore, strongly recommend the APARCH model based on the skewed Student-t distribution for modeling returns distribution.

Given above considerations, it is therefore needed to first model the return distribution of DJIM and DJSI indices in order to deliver accurate VaR forecasts. Following the Giot and Laurent [12, 13] methodology, two symmetric (RiskMetrics and Student-t APARCH) models and one asymmetric (skewed Student-t APARCH) model are covered in this study. The methodologies and their relative performance in capturing risk are explained below.

2.1. *RiskMetrics*

Consider an AR(p) structure of index returns, r_t, that has the following specification:

$$r_t = \rho_0 + \sum_{i=1}^{t} \rho_i r_{t-i} + \varepsilon_t. \tag{2.1}$$

In its most simple form, it can be shown that the basic RiskMetrics model is the IGARCH model with normal distribution where the autoregressive parameter is set at a prespecified value $\lambda = 0.94$ and the coefficient of ε_{t-1}^2 is equal to 0.06. In this specification, we have that z_t is i.i.d. $N(0,1)$ and the conditional variance h^2 is defined as

$$h_t^2 = (1-\lambda)\varepsilon_{t-1}^2 + \lambda h_{t-1}^2. \tag{2.2}$$

For this model, the one-step-ahead VaR as computed in $t-1$ for long trading positions is given by $z_a h_t$, and for short trading positions it is equal to $z_{1-\alpha} h_t$ with z_α being the left quantile at $\alpha\%$ for the normal distribution and $z_{1-\alpha}$ being the right quantile at $\alpha\%$.

2.2. *Student-t APARCH*

The APARCH(p,q) model of Ding *et al.* [6] is an extension of the GARCH(p,q) model of Bollerslev [4] and specifies the conditional variance as follows:

$$h_t^\delta = \alpha_0 + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j h_{t-j}^\delta, \tag{2.3}$$

where $\alpha_0 > 0$, $\delta > 0$, $\beta_j \geq 0$ for $j = 1, \ldots, p$, $\alpha_i \geq 0$ and $-1 < \gamma_i < 1$ for $i = 1, \ldots, q$. In this model δ plays the role of a Box–Cox transformation of h_t, while γ_i reflects the so-called leverage effect. A positive (respectively, negative) value of γ_i means that past negative (respectively, positive) shocks have deep impact on current conditional volatility than positive shocks. Because the distribution of asset returns usually characterized fat tail we work with Student-t APARCH, where ε_t is i.i.d. $t(0, 1, \nu)$.

For the Student-t APARCH model, the one-step-ahead VaR as computed in $t-1$ for long trading positions is given by $t_{a,\nu} h_t$, and for short trading positions it is equal to $t_{1-\alpha,\nu} h_t$ with $z_\alpha$being the left quantile at $\alpha\%$ for the Student-t distribution with ν degree of freedom and $t_{1-\alpha,\nu}$ being the right quantile at $\alpha\%$.

2.3. *Skewed student-t APARCH*

According to Lambert and Laurent [20], the innovation process ε_t is said to be $SKST(0, 1, \xi, \nu)$ standardized skewed Student-t distributed if

$$f(\varepsilon/\xi, \nu) = \left\{ \begin{array}{ll} \dfrac{2}{\xi + \dfrac{1}{\xi}} \mathrm{sg}[\xi(s\varepsilon + m|\nu)] & \text{if } \varepsilon_t/h_t \geq -m/s \\ \dfrac{2}{\xi + \dfrac{1}{\xi}} \mathrm{sg}[\xi(s\varepsilon + m|\xi/\nu)] & \text{if } \varepsilon_t/h_t < -m/s \end{array} \right\}, \tag{2.4}$$

where m is the mean of the non-standardized skewed Student-t distribution, that is, $m = \frac{\Gamma((v+1)/2)\sqrt{v-2}}{\sqrt{\pi}\Gamma(v/2)}$ and s is the variance of the non-standardized skewed Student-t distribution, that is, $s = (\zeta^2 + \zeta^{-2} - 1 - m^2)^{0.5}$.

For the skewed Student-t APARCH model, VaR for long and short positions is given by $t_{a,\nu,\xi} h_t$ and $t_{1-a,\nu,\xi} h_t$, respectively, with $t_{a,\nu,\xi}$ being the left quantile at $\alpha\%$ for the skewed Student-t distribution with ν degrees of freedom and asymmetry coefficient ξ; $t_{1-a,\nu,\xi}$ is the corresponding right quantile.

2.4. *The relative performance of VaR models*

In order to assess models' performance, we use a method that is currently a yardstick in the VaR literature. In the first step, the empirical failure rate was estimated for both the left and right tails of the returns distribution. In the second step, the Kupiec [19] LR statistic was computed to compare the performance. By demarcation, the failure rate is the number of times the absolute value of returns exceeds the predicted one-day-ahead VaR. If the VaR model is correctly specified, the failure rate should equal the prespecified VaR level, $\alpha\%$. Following Giot and Laurent [12, 13] we define a failure rate f_l for the left tails, which is equal to the percentage of negative returns smaller than the one-step-ahead VaR for buying positions. Correspondingly, we define f_r as the failure rate for right tails as the percentage of positive returns larger than the one-step-ahead VaR for selling positions.

Since the calculation of the empirical failure rate is defined as a sequence of yes/no observations, we can use the Kupiec [19] statistics which has a χ^2 distribution to test the null hypothesis that the failure rate equals a prespecified VaR level.

3. Data and Its Time Series Properties

3.1. *Data*

Dow Jones Indexes initiated their DJIS index in 1999. This index represents the first worldwide Islamic equity index that is compatible with Islamic investment guidelines. Formerly, Islamic funds sponsors established their own internal benchmarks to measure their Islamic funds performance raising doubts about potential conflicts of interest. Today, the DJIS is used by investment firms in 16 countries as an underlying index and a benchmark for a variety of financial products, including mutual funds, separate accounts, structured products, and an exchange-traded fund listed on Euronext. In total, well over $US4 billion are presently managed in DJIS-based investment vehicles.

The DJIS is a "low-debt, non-financial, social-ethical index" in the broad sense. To be included in the DJIS index, a company must undergo three screening filter:

1. Its primary business must be halal (permissible according to Islamic law-Shari'ah), therefore, companies engaged in gambling, alcohol, armaments, tobacco, pornography or pork are excluded.
2. A company must meet specific financial constraints. All the following must be less than 33%:
   - total debt divided by trailing 12-month average market capitalization.
   - the sum of the company's cash and interest-bearing securities divided by the trailing 12-month average market capitalization.
   - accounts receivable divided by the trailing 12-month average market capitalization.

3. Finally, companies are continuously monitoring according to these criteria. Whenever a company exceeds these limits, it is removed from the index and replaced by another.

Therefore, the DJIS index provides comprehensive coverage across countries, regions, and Shari'ah-compliant industries. Diversified exposure is ensured by selecting components from lists of stocks grouped by industry group and by country. Presently, the index includes stocks from 43 countries and covers 10 economic sectors, 18 market sectors, 40 industry groups and 70 subgroups. Additionally, the index includes only actively traded stocks that are easily accessible to investors. The DJIM-world index, which excludes very small and thinly traded stocks, is used as the selection universe for the components of the DJIS index.

3.2. *Univatiate analysis*

In order to investigate the risk and reward dynamics in the DJIS index and compare with the unrestricted DJIM index, we collected daily data for these two indices from 1 January 1996 to 20 May 2005, and they are 2449 observations. The data are available from Dow Jones Inc., the publisher of the two indices.

The daily returns are defined by $r_t = \log(p_t/p_{t-1}) \times 100$, where p_t denotes the value of the index at day t. Table 1 presents some key statistics of the raw data. On the risk basis (measured by the annualized standard deviation), the DJIS index appears to be less risky in comparison to the DJIM index. However, both appear

Table 1. Descriptive statistics for daily returns.

	DJIS	DJIM
Mean	0.0265	0.0185
Maximum	4.4642	4.3358
Minimum	−5.3237	−4.3609
Std. dev.	0.9988	0.8748
Kurtosis	5.1495***	−0.1844***
Skewness	−0.2030***	5.2846***
Jarque–Bera	488.26***	546.50***
$Q\,(20)$	35.031**	93.67***
$Q^2(20)$	102.65***	119.32***
ARCH(6)	235.888***	287.722***

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The mean is the equally weighted average of observation over the sample period. JB is the Jarque–Bera [17] normality test, which follows a chi-squared distribution, with two degrees of freedom. Q and Q^2 denote, respectively, the Ljung–Box and Ljung–Box^2 statistics. ARCH is a test for conditional heterocedasticity in returns which is based on the regression of squared residuals on lagged squared residuals. The statistics is asymptotically distributed as χ^2.

to have similar statistical properties as far as the third and fourth moments are concerned. In particular, both indices are negatively skewed, and the large returns (either positive or negative) guide to a large degree of kurtosis, leading to a high valued Jarque and Bera [16] test, which indicates the non-normality of the distribution. The Ljung–Box Q-statistics of order 20 on the level and squared series indicate a high serial correlation in both the first and second moments. Moreover, the Engle [8] LM test indicates the presence of the ARCH process in the conditional variance. These results indicate that a GARCH-type modeling should be considering in VaR estimates.

Descriptive graphs (index level, daily returns, QQ-plot against the normal distribution, and Kernel density function of the daily returns distribution) for each index are given in Fig. 1. Volatility clustering is immediately obvious from the graphs

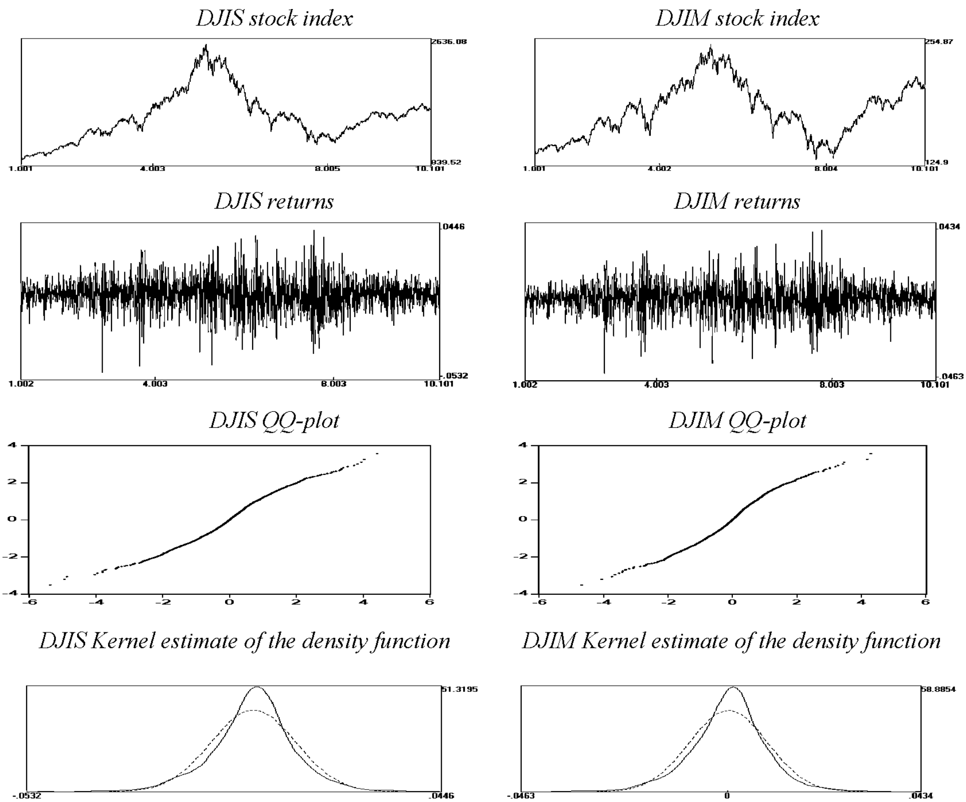

Fig. 1. DJIS and DJIM are the Dow Jones Islamic Index and the Down Jones World Index.[6]

[6]Market returns calculated by $r_t = \log(P_t/P_{t-1})^* 100$, where P_t and P_{t-1t} are the value of the index at time t and t_{t-1}, respectively. QQ-plot is the Quantile–Quantile plot against the normal distribution. Kernel estimate of the density function of the distribution with bandwidth $h = c \cdot \hat{n}\,(-1/5)$, where $c = 1$, compared with the corresponding normal density (dashed curve). The period is spanned from 1/1/1996 to 20/5/2005.

of daily returns. The Kernel density graphs and the QQ-plot against the normal distribution show that both indices exhibit fat tails. Moreover, QQ-plots indicate that fat tails are asymmetric.

4. Empirical Analysis

In order to perform the VaR analysis, RiskMetrics and APARCH with Normal, Student-t, and skewed Student-t distributions are needed to be estimated as a first step. Table 2 presents the (approximate quasi-maximum likelihood) estimation results for the parameters of the APARCH model,[7] while Tables 3 and 4 report some useful in-sample statistics. Several conclusions can be drawn by analyzing these results. First, for both series, an AR(3) was found to be sufficient to correct the

Table 2. APARCH(1,1) estimation results.

	DJIS			DJIM		
	Normal	Student-t	Skewed-t	Normal	Student-t	Skewed-t
ρ_0	0.02211* (0.0688)	0.03740*** (0.0011)	0.02705** (0.0212)	0.00282 (0.6084)	0.01064 (0.1811)	0.00594 (0.3744)
ρ_1	0.20761*** (0.0000)	0.21876*** (0.0000)	0.21159*** (0.0000)	0.22051*** (0.0000)	0.21577*** (0.0000)	0.20821*** (0.0000)
ρ_2	−0.03685* (0.0564)	−0.05499** (0.0131)	−0.06063** (0.0102)	−0.05704** (0.0180)	−0.07147*** (0.0021)	−0.07795*** (0.0012)
ρ_3	−0.01215 (0.5924)	0.00364 (0.8640)	0.00305 (0.8946)	0.00791 (0.7343)	0.01970 (0.3845)	0.01697 (0.4625)
α_0	0.00562* (0.0667)	0.00544* (0.0620)	0.00582* (0.0527)	0.00434** (0.032)	0.00510*** (0.0020)	0.00526*** (0.0018)
α_1	0.07932*** (0.0000)	0.07604*** (0.0000)	0.08011*** (0.0000)	0.05680*** (0.0000)	0.05737*** (0.0000)	0.05874*** (0.0000)
β_1	0.91239*** (0.0000)	0.92056*** (0.0000)	0.91720*** (0.0000)	0.90653*** (0.0000)	0.93787*** (0.0000)	0.93544*** (0.0000)
γ_1	0.43516*** (0.0004)	0.74192*** (0.0001)	0.72903*** (0.0001)	0.71873 (0.0006)	0.95477*** (0.0000)	0.93661*** (0.0000)
δ	1.39358*** (0.0000)	1.17936*** (0.0000)	1.19103*** (0.0000)	1.36034*** (0.0000)	1.06168*** (0.0000)	1.09282*** (0.0000)
ν	—	7.82442*** (0.0000)	8.75159*** (0.0000)	—	10.20742*** (0.0000)	10.07807*** (0.0071)
ξ	—	—	−0.13687*** (0.0013)	—	—	−0.07807*** (0.0000)
S.C.	0.9825	0.9834	0.9972	0.9768	0.9841	0.99184

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are given in parentheses. S.C. is the stationary constraint value and should be < 1.

[7] The RiskMetrics model does not require any estimation for the conditional volatility specification as it is tantamount to an IGARCH model with some predefined values.

Table 3. Estimation statistics-models comparison.

	Skewness	Kurtosis	J–B	$Q\,(20)$	$Q^2(20)$	ARCH(6)	$P(50)$	Akaike	L–L
DJIS									
Normal	−0.378***	1.675***	333.15***	20.5*	15.8*	2.566*	59.9**	0.8959	−1089.0
Student-t	−0.381***	2.106***	512.18***	18.0	9.6	1.143	55.4*	0.8933	−1085.8
Skewed-t	−0.218***	2.658***	212.49***	11.2	7.2	0.627	41.3	0.8920	−1083.3
DJIM									
Normal	−0.324***	1.368***	233.96***	38.2**	18.0**	1.924*	77.1***	0.6153	−746.5
Student-t	−0.315***	1.972***	204.14***	21.3	16.1	2.07*	56.0*	0.5949	−720.4
Skewed-t	−0.304***	2.409***	194.08***	21.5	15.2	1.11	42.6	0.5927	−716.8

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. JB is the Jarque–Bera [16] normality test, which follows a chi-squared distribution, with two degrees of freedom. Q and Q^2 denote, respectively, the Ljung–Box and Ljung–Box^2 statistics. ARCH is a test for conditional heterocedasticity in returns, which is based on the regression of squared residuals on lagged squared residuals. The statistics is asymptotically distributed as χ^2. $P(50)$ is the Pearson Goodness-of-fit with 50 cells. AIC and L–L are the Akaike Information criterion and the log-likelihood value.

Table 4. Failure rates of VaR estimates.

	5%	2.5%	1%	0.5%	0.25%
Left tail					
DJIS					
RiskMetrics	0.00563	0.00293	0.01424	0.01668	0.03289
Normal APARCH l	0.03487	0.08857	0.06475	0.01705	0.01261
Student-t APARCH	0.20920	0.10149	0.01286	0.00195	0.05720
Skewed-t APARCH	0.75934	0.67041	0.48892	0.30378	0.15723
DJIM					
RiskMetrics	0.04056	0.03804	0.07944	0.08032	0.21693
Normal APARCH l	0.09201	0.46645	0.51115	0.12872	0.33304
Student-t APARCH	0.11458	0.05110	0.01286	0.00911	0.02864
Skewed-t APARCH	0.67959	0.77594	0.48892	0.07920	0.06259
Right tail					
DJIS					
RiskMetrics	0.07219	0.01443	0.00063	0.00042	0.00097
Normal APARCH l	0.36244	0.20987	0.05807	0.04375	0.00798
Student-t APARCH	0.15962	0.20987	0.03781	0.36343	0.10766
Skewed-t APARCH	0.75934	0.57161	0.48892	0.53882	0.64260
DJIM					
RiskMetrics	0.02252	0.03987	0.00032	0.00000	0.00000
Normal APARCH l	0.83691	0.48084	0.02997	0.04375	0.00289
Student-t APARCH	0.19094	0.57161	0.51023	0.23188	0.21693
Skewed-t APARCH	0.46761	0.66431	0.64752	0.53882	0.79427

Note: The numbers are the P-values for the null hypothesis $f_l = \alpha$ (i.e., the failure rate for the left and right tails are equal to α). Note that a P-value smaller than 0.05 indicates that the corresponding VaR model does not perform adequately out-of-sample.

serial correlation in the conditional mean. Second, the use of asymmetric GARCH models seems to be justified. For both series, all asymmetric coefficients are significant at standard levels. Moreover, the Akaike information criteria (AIC) and the log-likelihood values highlight the fact that the skewed Student-t APARCH model has better estimated the series than the Gaussian and Student-t. Particularly, for both series, the skewed Student-t APARCH model seems to perform well in describing the dynamics of the second moment for each series as shown by the Box–Piece statistics of the squared residuals, which are all non-significant at 5% level. Fourth, the stationary constraints are observed for every model and for every density. In particular, Table 2 reports the stationary condition of the APARCH model. The values (ranging from 0.98 to 0.99) suggest long persistence of the volatility of both indices. Fifth, the autoregressive effect in the volatility specification is relatively strong as β_1 is around 0.93, suggesting a relatively strong memory effect. Sixth, α_1 is positive and significant, indicating an advantage effect for negative returns in the conditional variance specification. Seventh, ζ is negative and significant, which implies that the symmetry in the Student distribution is needed to fully model the distribution of returns. Finally, δ is always significantly different from 2. This result suggests that instead of modeling the conditional variance as a GARCH process, the APARCH is more relevant.

In summary, for both the series under consideration, the results indicate the need for a model featuring a negative leverage effect for the conditional variance combined with an asymmetric distribution for the underlying error term. The skewed Student-t APARCH seems to cover these characteristics, and therefore it is recommended to model the return series in estimating VaR.[8]

As a second step, we use the above estimation results to compute the one-step-ahead VaR for RiskMetrics and APARCH with Normal, Student-t, and skewed Student-t distributions at different tail quantiles. As mentioned earlier, if the VaR model is correctly specified, the failure rate should be equal to the prespecified VaR level (probability). To assess the relative performance of each model, we use Kupiec's test, which performs well most of the time.[9] However, it is known that it fails to reject/accept the null hypothesis when it is false/true due to its low local power. Therefore, it may be difficult to identify a poorly performed model. We also compute confidence interval estimates for the empirical failure rates as follows: at the 5% level and if T yes/no observations are available, a confidence interval for $\hat{f}$ is given by $[\hat{f} - 1.96\sqrt{\hat{f}(1-\hat{f})/T}, 1.96 + \sqrt{\hat{f}(1-\hat{f})/T}]$. In this paper, these tests are successfully applied to the failure rate f_l for left tails (long trading positions) and then to f_r, the failure rate for right tails (short trading positions).

[8]This result is highly consistent with that of Giot and Laurent [12, 13] who highly recommended to use skewed Student-t APARCH in estimating VaR.

[9]In the literature of VaR, this test is also called the Kupiec LR test if the hypothesis is tested using a likelihood ratio test (see [19]).

Table 4 presents complete VaR results (i.e., P-values for the Kupiec LR test) for both indices.[10] The results indicate that VaR models based on the normal distribution have the worst performance in modeling the DJIS and DJIM returns, with left tails being somewhat better handled than right tails. The Student-t model improves very slightly on the performance of normal based models, and considerably its performance is still not satisfactory for both tails in the indices under consideration. The results from the tables also show that the skewed Student model improves considerably on the normal and Student distributions for both left and right tails. The model performs correctly with 100% accuracy in both cases for the positive (right tail) and the negative (left tail) returns. These results provide a further confirmation to the above conclusion that the skewed Student-t APARCH is the more reliable model in VaR estimations.

Assuming a one-day holding period and using a moving window of 500 day data, we calculate 1000 daily VaR forecasts from the skewed Student-t APARCH model for both series at different confidence levels.[11] We concentrate in the left and right tails distributions (i.e., long and short positions in the underlying assets). For each period, 100 subsamples each with 100 observations are drawn with replacement from the last 500 day history simulated profit/loss series. The average one-day-ahead VaR forecasts are given in Table 5. As expected, the VaR forecast increases with the increasing confidence level. More importantly, at any level of significance level, the results show that the value of VaR is greater for DJIM than for DJIS. This result indicates that the Islamic Index is less risky than the DJIM index, and thereby, the risk performance of the Islamic index is relatively competitive. It appears, however, that the filtering criteria adopted to eliminate Shari'ah-non-compliant companies have resulted in a subset of unique companies and did not

Table 5. VaR estimates produced by the skewed-t APARCH model.

	5%	2.5%	1%	0.5%	0.25%
Left tail					
DJIS	1.8881	1.2148	1.3969	3.4742	2.0125
DJIM	3.6404	2.7249	1.8276	4.0850	3.2150
Right tail					
DJIS	9.395	11.838	8.257	20.818	2.6176
DJIM	11.506	12.700	10.620	22.107	25.068

The interpretation of the units of VaR is, using for example the first figure in the table below (1.8881), that there is a 95% chance that the loss of a portfolio will not exceed 1.8881% in a day.

[10] We also estimate VaR models using the out-of-sample procedure. The results for this procedure being quite similar to those obtained from the in-sample procedure are not reported. Interested readers can obtain them on simple request.

[11] We also adopt another four different window sizes, i.e., 500, 1500, 2000, and 2500, and the findings for these windows do not differ from the window size of 1000 observations significantly.

adversely affect the performance of the Islamic index in comparison to the world equity market. In other words, even though it is investment restrictive and it has limited relative diversification, the exclusion of several industries from the DJIS index did not harm its diversification, but actually contributes to the risk reduction.

5. Conclusions

Introducing the Dow Jones Islamic World Market Index has quickly gained a great response from Muslim investors worldwide. The index provides to the needs of investors looking for Shari'ah-compliant stocks. Furthermore, the index provides investors a benchmark to judge how their Islamic funds perform against an Islamic Index. In this paper, we use recent risk measures to examine how this selection restriction affects the risk of Islamic investments represented by the Dow Jones Islamic Index.

As expected, the empirical results suggest that the Islamic index presents unique risk characteristics; the examination reflects a risk level that is significantly less than the board market basket of stocks. We interpret the results mainly to the profit-and-loss sharing principle of Islamic finance where banks share the profits and bear losses (Mudarabah) or share both profits and losses (Musharaka) with the firm.

Two immediate implications emerge from this study. First, the findings may help investors to evaluate the risk performance of the most popular Islamic index available today with the world equity market. Second, filtering criteria adopted to eliminate Shari'ah-non-compliant companies have no loss, and Muslim investors are no worse off investing in an Islamic basket of stocks in comparison to a much larger basket.

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